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Application of Deep Belief Network for Sustainable Development via Deep Learning to Export Credit Risk Assessment Under the Belt and Road Strategy

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Abstract. The purpose of the study is to reduce the export credit risk of enterprises, and the export credit risk assessment of enterprises under the belt and road strategy based on deep learning is discussed. First, the research background and deep belief networks are introduced. Second, the contrast divergence algorithm based on the deep belief model is improved on the restricted Boltzmann machine. Finally, the deep belief network of classification and partition is constructed and simulated. The results show that the test accuracy of the classification and partition of the restricted Boltzmann machine (CPRBM) constructed is higher than that of the restricted Boltzmann machine (RBM). When the accuracy of the algorithm is verified under the condition of unbalanced two classification samples in a relatively small amount of datasets, the accuracy of the CPRBM algorithm is 93.71%, and the accuracy of the RBM algorithm is 89.86%. In the optimization stage of the deep belief networks, the convergence rate of the CPRBM is slower than that of the RBM. Since the optimized system increases the penalty term in the first training stage of the deep belief networks, the penalty term is canceled in the second stage of optimization. At three time points, the algorithm accuracy of the CPRBM is higher than that of the RBM. The simulation results are consistent with the previous experimental results. Although the accuracy is not high at the third time point, the CPRBM algorithm still has some advantages. Compared with the accuracy of the support vector machine (SVM) and the deep extreme learning machine (DELM), the CPRBM algorithm based on deep belief networks has the highest accuracy at any time point. The CPRBM algorithm constructed has obvious advantages compared with common models, and the overall performance of the algorithm is better. The conclusions provide the support for the sustainable development of the economy under the Belt and Road strategy.

Keywords. Deep learning, deep belief networks, credit risk assessment, sustainable development

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1. Introduction

“The Belt and Road” is the abbreviation of “21st Century Maritime Silk Road” and “Silk Road Economic Belt”. The Belt and Road strategy is proposed by China, and it aims to create a community of interests to promote the common development of the regional economy by establishing multilateral relations with relevant countries [1]. Since the Belt and Road Initiative is built in 2015, more and more Chinese enterprises begin to go abroad, and China has gained a new identity as a capital exporter [2]. With the continuous advancement of the Belt and Road strategy, China's overseas investment projects increase rapidly [3]. The vigorous development of foreign trade makes the competition of export enterprises fiercer and diversified. In addition to the traditional competitive projects, such as services, prices, and products, the new settlement method becomes a hot project in the market competition among export enterprises. The Open Account Trade (OA) settlement method, which is welcomed by export enterprises, is similar to the payment of goods [4]. This settlement method provides certain financing convenience to customers. It can increase the price of products and the competitiveness and profit space of enterprises simultaneously [5]. Similar to the payment by delivery, the OA settlement method has certain requirements for the credit of export enterprises. Therefore, it is also known as a credit transaction [6]. The credit market of some western countries with sound credit environments is relatively mature. The use of credit transactions in trade accounts for more than 80%. The credit transaction has become an important means for enterprises to stand out in the international trade competition [7].

Credit risk is the main problem in credit transactions and is may occur in many links of export trades, such as customer development, contract signing, and money recovery [8]. Most enterprises lack the prior risk assessment of foreign buyers and are blind in the trade process [9]. Any problem in the credit risk management system of export enterprises will lead to credit risks. For example, in international trade, domestic enterprises lack a full understanding of the strength of foreign buyers. Once there occurs debts, domestic enterprises will bear huge losses [10]. Therefore, the study on export credit risks is very important, and the credit risk assessment system has far-reaching significance for the sustainable development of the regional economy [11].

The export credit risk assessment system is very important for the economic development of enterprises under the Belt and Road strategy. Based on the deep belief network and deep learning, the export credit risk assessment system under the Belt and Road strategy is studied. First, the current situations of the export risk assessment system and the deep belief network are introduced. Then, the credit risk assessment systems are constructed. Finally, the model is simulated. The innovation of this study is to propose a deep belief network based on the classified partition restricted Boltzmann machine, which can solve the problem of insufficient mining data labels when the restricted Boltzmann machine performs supervised learning. The research promotes the sustainable development of the export economy under the Belt and Road strategy.

2. Research Status

2.1 Export Credit Risk Assessment

Foreign studies on export credit risks take transaction cost as the starting point and believe that transaction cost is a cost based on price mechanisms [12]. In international trade, the transaction costs are different under different settlement methods due to the asymmetry and status between import and export parties. Both sides pursue lower transaction costs in the trade process, so the export credit risk increases. Some studies proposed the view of bounded rationality based on rational economists. It is a specific behavior in the trade, and the trade between the two sides is affected by "opportunism", which is realized through the game between altruism and egoism to maximize the benefits [13]. The credit risk management system minimizes risks through measurement, identification, handling, and risk control [14]. Australia suggested that a comprehensive risk management system should be established to maximize the company's opportunities from the company's business. With the development of science and technology, foreign countries shift their research perspective to the quantification of risks and the construction of models [15]. And the common models include the Credit risk model, Z-score model, and feature analysis model. It is generally believed that export credit insurance can guarantee the foreign exchange safety of enterprises [16]. Trade companies can transfer credit risks to credit risk institutions when foreign trades are conducted to ensure the normal operation of trade activities [17].

Domestic research on export credit risks starts late, the initial research on the trade credit risk shows that the contract risk is the most important export credit risk [18]. Some studies hold that the export credit risk comes from the unpaid bills of foreign importers due to their reasons [19]. Some studies also believe that the export credit risk is related to the national political risk. The analysis of credit risks is based on the characteristic analysis model and risk early warning index system. Export risks can be divided into carrier credit risks, importer credit risks, and bank credit risks [20]. Some scholars believe that China's weak awareness of prevention is one of the reasons for export credit risks and the imperfect credit risk management system is the main reason for the internal and external credit dilemma of enterprises [21]. At the end of the last century, the main method for risk management in China is the expert analysis method, and finally, the Logit analysis method with smaller engineering quantity and easier implementation is added [22]. After the 21st century, China's research on export credit risk begins to turn to quantitative analysis [23]. And some scholars put forward a scientific credit management model for Chinese enterprises combined with the advanced experience of the West [24]. The research on export credit risk transfer mainly focuses on improving the risk management mechanism. The overall credit risk prevention includes risk avoidance, timely compensation for losses, and power recovery and loss reduction to enhance the competitiveness of Chinese enterprises [25].

The export risk assessment system in foreign countries has made some achievements. The current domestic and foreign research focuses on the optimization and improvement of the model, and the practical application effect is good. However, the traditional research methods have certain limitations. The actual data used in the research are few, and the analysis results are not convincing. After the arrival of the era of big data, artificial intelligence (AI) develops rapidly, and the model based on new technologies are superior. Therefore, the deep belief network is used to study the export credit risk under the Belt and Road strategy.

2.2 Deep belief network

Neural networks begin to develop in the middle of the 20-th century. At the end of the 20-th century, the concept of AI is proposed. It has obvious advantages for massive data processing [26]. As the core of AI, machine learning is rising. Deep learning is a new method in machine learning [27], and it is a method based on artificial neural networks, which include the feedforward deep network, feedback deep network, and bidirectional deep network [28]. The deep belief network belongs to the bidirectional deep network in deep learning. The deep belief network is composed of a layer of the supervised Back Propagation Neural Network (BPNN) and a multi-layer unsupervised restricted Boltzmann machine [29].

The Boltzmann machine is proposed at the end of the 20-th century. Its convergence is low and the learning process is easy to diverge. Therefore, the restricted Boltzmann machine is proposed to solve the problem of divergence. It greatly improves the learning performance only by connecting the adjacent two layers [30]. In the 21-st century, some scholars propose a hierarchical RBM deep belief network algorithm based on GL (greedy learning) and study the learning ability of neural networks with multiple hidden layers. Through the method of layer-by-layer initialization, the difficulty of deep neural networks in training is also overcome [31]. Researchers find that the restricted Boltzmann machine is more efficient after comparing the divergence with other algorithms in 2008. With the development of deep belief networks, some studies prove that the classification-restricted Boltzmann machine is used to supervise learning. That is, the binary random variables are introduced into the hidden layer, and the class labels and input features are used as units for learning [32]. The research on deep learning in China mainly focuses on the research of deep belief networks, and the Boltzmann machine algorithm is improved based on some foreign research. There are also some studies on the application of deep belief networks, including face recognition and fatigue driving.

At present, many scholars in China and foreign countries pay more attention to the study of deep belief networks and many scholars do some empirical research in many fields under deep learning, but the application of deep belief networks in export credit risk assessment systems is few. In previous studies, supervised learning is not used in the training of deep belief networks, and important information contained in labels is not included in the learning. Therefore, deep belief networks are used to analyze export credit risks by employing the supervised learning method of restricted Boltzmann machines.

3. Implementation of the Export Credit Risk Assessment Model Under the Belt and Road Strategy

The structure of deep belief networks is shown in figure 1.

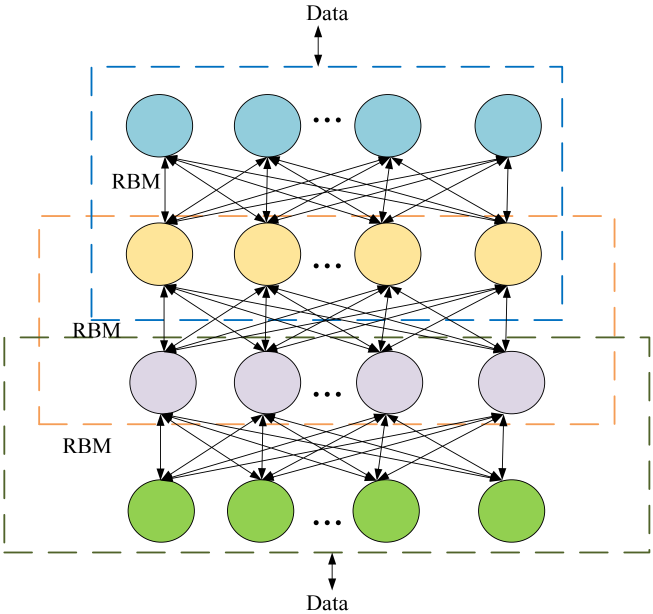

Figure 1. Structure of deep belief networks

Figure 1 shows that the deep belief network consists of a layer of supervised BP networks and a multi-layer unsupervised restricted Boltzmann machine. The deep belief networks integrate the multi-layer neural network of feature learning and deep learning with the layer-by-layer unsupervised pre-training mechanism to solve the problem that the multi-layer neural network is difficult to train by the gradient descent method.

The main component of the deep belief network is the restricted Boltzmann machine. The neurons in the Boltzmann machine are random neurons, and the output is a binary state. It is represented by 1 and 0 of the binary, and the state value is obtained by combining the probability statistics algorithm. The structure of the restricted Boltzmann machine is shown in figure 2.

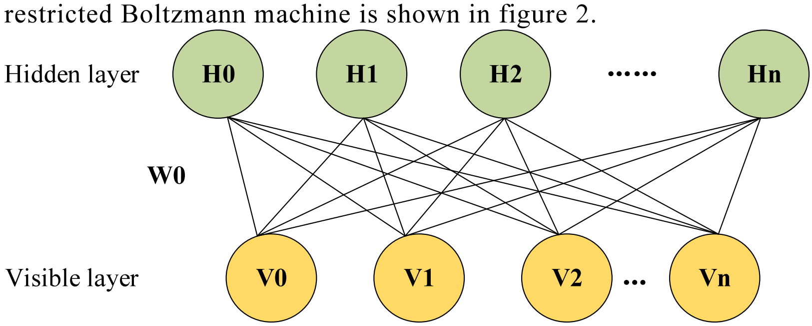

Figure 2. Structure of the restricted Boltzmann machine

Figure 2 shows that the neurons of the restricted Boltzmann machine are symmetrically connected, consisting of an implicit layer and a visible layer without self-feedback. The Boltzmann machine has strong unsupervised learning ability but slow training speed and difficulty to obtain the corresponding samples, which can be overcome by the restricted Boltzmann machine. The restricted

Boltzmann machine model is a special case of the Boltzmann machine. H is the feature, V is the observation data, and W is the weight. The characteristics of the restricted Boltzmann machine are that there is no connection between the nodes in the layer, and the independent nodes lay the foundation for the accurate calculation of the distribution.

3.1 Improvement of the RBM Algorithm

The deep belief network has two learning steps, namely the bottom-up generation and the top-down generation. In the process of bottom-up generation, the label information of samples cannot be effectively used, and an accurate evaluation cannot be carried out. Therefore, the RBM algorithm needs to be improved.

At first, the theory of Sparse Restricted Boltzmann Machines (SRBM) is introduced. The sparse representation model is the system feature based on biological vision, and the signal can be represented by signal combination. After sparse representation, the system contains rich feature information of the original signal. The feature representation of RBM is generally distributed but not sparse. Only a few of the hidden layers of RBM are in an active state and they are distributed, satisfying the sparse idea. Here, the sparse penalty term is introduced to set the deviation of the average activation probability based on the logarithmic likelihood function. The given training sample is calculated by Equation (1).

$$m^{(1)},m^{(2)},...,m^{(T)} \tag{1}$$

In equation (1), T is the number of samples, and the objective function of SRBM is calculated by Equation (2).

$$\min_{w_{ij}c_{ji}b_j}\text{imize}-\sum_{t=1}^{T}\log\sum_h f(m^{(t)},h^{(t)})+\delta\sum_{j=1}^{T}\left|f-\frac{1}{T}\sum_{t=1}^{T}E[f_j^{(t)}|m^{(t)}]^2\right| \tag{2}$$

In equation (2), E is the conditional expectation, f is the deviation and δ is the regularization coefficient. First, the logarithmic likelihood function is trained by the contrast divergence algorithm, and then the regularization term is used for gradient descent. Studies have shown that this method plays a greater role in promoting machine learning. The introduction of group sparsity into RBM learning has achieved good results in training datasets.

In previous methods, RBM plays the role of feature extractor and trains RBM in the classification. The training set uses unlabelled training data and then combines other algorithms to conduct supervised learning on training data. This method ignores the role of labels, so binary random variables are introduced and tag data are added to simplify the calculation process.

3.2 Classification and Partition of the RBM Algorithm

Based on the partition of the human brain function, the partition learning function is added to the RBM, labels are introduced into the training process, and the RBM algorithm is improved to include the supervised algorithm. The comparative divergence learning model based on the RBM is shown in figure 3.

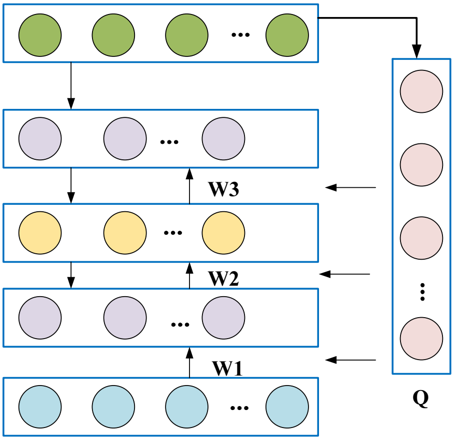

Figure 3. Comparative divergence learning model based on RBM

Figure 3 shows that the model contains an input layer, an output layer, and an implicit layer. The input sample is X, the sample label is Y, the hidden layer is H, and the connection weight is W. A network training based on the RBM is divided into the first layer of m layer and h1 layer and the second layer of h1 and h2. The probability can be calculated by equations (3) (4) and (5).

$$f(h_1=1|m)=sigmrnd(mw^{1T}) \tag{3}$$

$$f(h_1'=1|h_1)=sigmrnd(h_1w^1) \tag{4}$$

$$f(h_1'=1|m_1')=sigmrnd(m_1'w^{1T}) \tag{5}$$

According to the principle of the reconstruction error, each parameter is adjusted. On this basis, the penalty term is generated by the classification and partition, and the classification is realized by obeying the fixed distribution. The parameter setting required for the classification and partition of the RBM is the deviation and mean of the Gaussian classification penalty vector of different classifications in each hidden layer. If the input label is S, the penalty vector of the hidden layer can be calculated by equation (6).

$$q=SQ \tag{6}$$

In equation (6), q is the generating function of the vector, and Q is the classification and partition matrix.

Based on the above, the RBM learning algorithm based on classification and partition is obtained. If the visible unit of the model is n, the hidden layer unit is a, the visible state is m, and the hidden layer state is h, the system function of a state can be calculated by equation (7).

$$E(m,h)=-\sum_{ij} w_{ij}m_i h_j q_{ij} \tag{7}$$

Then the joint probability density function of the hidden layer and the visible layer is calculated by equation (8).

$$f(m,h)=\frac{Exp(-E(m,h,q))}{Z} \tag{8}$$

In the above equation, Z is the normalization factor.

Combine with equations (3), (4), and (5), the activation probabilities of hidden units and visible units are determined. If the training sample is R, the RBM is trained to obtain the maximum likelihood function. The maximum value is obtained by using the random gradient ascending method, and the optimal parameters and the partial derivatives are obtained. In the RBM, the final parameter results are obtained by using the K-step contrast divergence algorithm, as shown in equations (9) (10) and (11).

$$w=w+\eta\Delta w \tag{9}$$

$$c=c+\eta\Delta c \tag{10}$$

$$b=b+\eta\Delta b \tag{11}$$

In the above equations, η is the learning rate, w, c, b are the adjustment parameters.

The overall process of the algorithm is shown in figure 4.

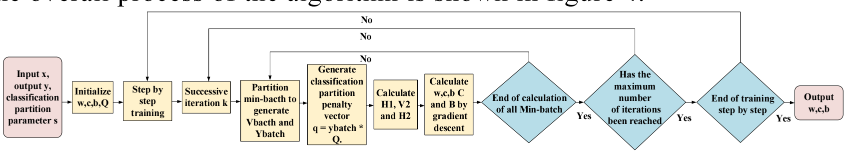

Figure 4. The flow of the RBM algorithm based on classification and partition

Fig. 4 shows that the overall calculation of the proposed algorithm is relatively simple, and the core is the obtained penalty vector. The parameter correlation of the algorithm should not be too high, and the deviation parameter is suitable for selecting large data, with 1/2 of the number of hidden layers as the best.

The datasets used for the algorithm verification are the data related to the export credit risk of enterprises under the Belt and Road strategy on the official website. The data verification is realized by Matlab software. The verification of the classification accuracy of the algorithm is divided into three situations, including the use of medium-sized sample data for testing (4190 samples), the use of small-scale sample data for testing (2094 samples), and the use of small-scale data for verification. The proportion of two types of samples is 1:3, and the samples marked as 1 are retained by 40%. Finally, the convergence rate of the model is evaluated, and the comparison object is the ordinary RBM algorithm.

3.3 Empirical study of the deep belief network based on the CPRBM in export credit risk assessment

Based on the above, the export credit risk assessment model is implemented in this section. The research object is the index that affects the credit risk, and the characteristic index is selected to analyze the basic information of enterprises. The structure of the specific model is shown in figure 5.

Figure 5 shows that data are preprocessing in the implementation of the export credit evaluation model, which is to unify the index to the same dimension and avoid the large numerical gap.

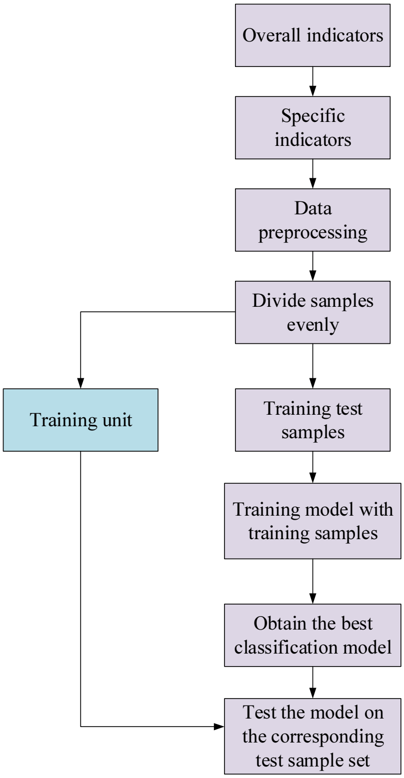

Figure 5. Export credit evaluation model based on deep belief networks

The sample of this study is the materials of 2910 export enterprises under the Belt and Road in 2020, and the industry classification is carried out. The 18 indexes are divided into three categories, as shown in table 1.

Table 1. Indexes of the export risk assessment system

Categories	Indexes
Credit and financial features	Short-term solvency
	Profitability
	Long-term solvency
	Operation ability
	Bank report
	Historical payment performance
Customers' features	Country risk
	Enterprises' performance
	Management ability
	Downstream markets
	Market position
	Industry background
Priority features	Terms of payment
	Payment guarantee
	Rate of profit
	Competition
	Market attractiveness
	Customer Replaceability

The data preprocessing is normalized by the standardized method. In terms of network parameter selection, the number and depth of the unit are small according to the research content. The initial values of weights and parameters are initialized according to the Bayesian theorem. The selection of learning rate is realized by increasing the dynamic learning rate. The gradient calculated by the training is combined with the last gradient and the last gradient is multiplied by a dynamic learning rate. The attenuation value is determined by the penalty function.

The cross-validation method is used to verify the validity of the model. The samples are divided into 10 groups. 9 groups are selected as the training group, and the remaining group is used for verification. The results are averaged as the experimental results. Here, two comparisons are conducted. The first is the comparison between the proposed algorithm and the common RBM. The second is the comparison between the proposed algorithm and other algorithms, including the SVM and the DELM.

4. Analysis of the performance and simulation results of the classification and partition of the RBM algorithm

4.1 Performance verification results of the CPRBM algorithm

The dataset is proved to be effective, and the verification results of the classification accuracy of the model are shown in figure 6.

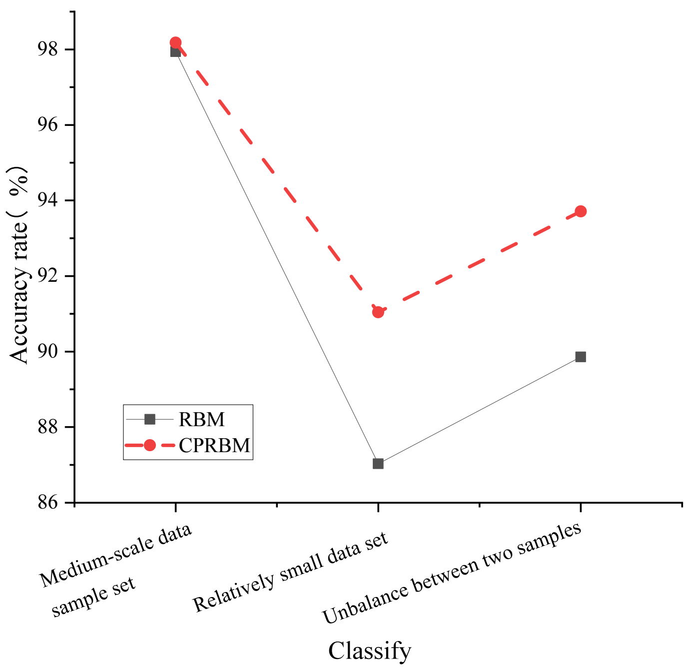

Figure 6. Accuracy of different samples

Figure 6 shows that the test accuracy of the CPRBM constructed is higher than that of RBM under any kind of sample set. When the medium-scale data are tested, the overall accuracy of the CPRBM is 98.18%, and the accuracy of RBM is 97.94%. When the relatively small amount of data are verified, the accuracy of the CPRBM is 91.04%, and the accuracy of RBM is 87.03%. When the algorithm is verified under the condition of unbalanced two classification samples in a relatively small amount of datasets, the accuracy of the CPRBM algorithm is 93.71%, and the accuracy of the RBM algorithm is 89.86%. The analysis shows that the classification accuracy of the algorithm constructed based on RBM is higher than that of the RBM algorithm, and the feasibility of this model is good. The verification results of medium-scale datasets show that the penalty vector introduced can stimulate the system to learn the characteristics of each classification. The small-scale data results show that the overfitting ability of the CPRBM is better. The verification results show that the CPRBM is superior in both overall accuracy and separate accuracy although the accuracy results of the CPRBM are also less than 88%.

The verification of the convergence rate of the model for training small-scale datasets is shown in figure 7.

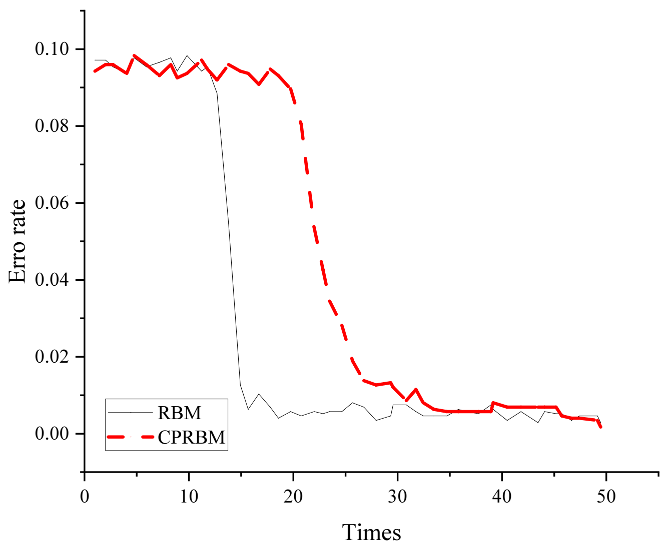

Figure 7. Comparison of the convergence speed of the model

Figure 7 shows that the convergence rate in the optimization of deep belief networks is slower than that of RBM. The RBM starts to converge rapidly in 15 minutes and tends to be stable in 30 minutes, while CPRBM starts to converge in 25 minutes and the convergence curve tends to be stable in about 30 minutes. The reasons may be that since the optimized system increases the penalty term in the first training of the deep belief network, the penalty term is canceled in the second stage of optimization. Therefore, in the second stage, the convergence rate of the system is slow, but this phenomenon is consistent with the principle of the algorithm.

4.2 Simulation results of the CPRBM algorithm

The overall risk evaluation system of three categories of indexes at three-time points is set up. The comparison results of RBM and CPRBM are shown in figure 8.

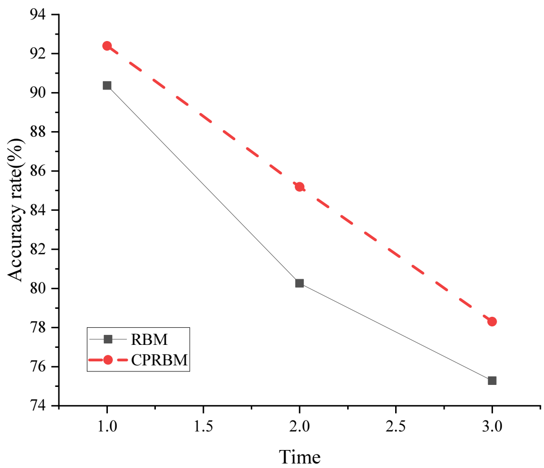

Figure 8. Comparison of the risk evaluation between RBM and CPRBM

Figure 8. shows that the risk evaluation accuracy of the CPRBM algorithm is higher than that of the RBM algorithm at three-time points. At the first time point, the accuracy of the CPRBM algorithm is 92.40%, and the accuracy of RBM is 90.37%. At the second time point, the accuracy of the CPRBM is 85.19%, and the accuracy of RBM is 80.26%. At the third time point, the accuracy of the CPRBM is 78.30%, and the accuracy of the RBM is 75.28%. The simulation results are consistent with the previous experimental results. Although the accuracy is not high at the third time point, the CPRBM algorithm still has certain advantages. This shows that the improved CPRBM algorithm based on RBM has high practicability.

The accuracy comparison of the risk evaluation of different models is shown in figure 9.

Figure 9 shows that compared with the accuracy of the SVM and the DELM, the CPRBM algorithm based on deep belief networks has the highest accuracy in evaluating credit risks at any time point. At the first time point, the accuracy of CPRBM is 92.40%, while the accuracy of the SVM is 88.76%, and the accuracy of the DELM is 86.40%. At the second time point, the accuracy of the CPRBM is 85.19%, and that of the SVM and the DELM is 83.43% and 80.21% respectively. At the third time point, the accuracy of the CPRBM is 78.30%, and the accuracy of SVM and DELM is low. The accuracy of the three algorithms is concluded that the accuracy of the CPRBM algorithm is the highest, that of the SVM algorithm ranks the second, and that of the DELM algorithm is the lowest. The CPRBM algorithm constructed has obvious advantages compared with common models, and the overall performance of the algorithm is better.

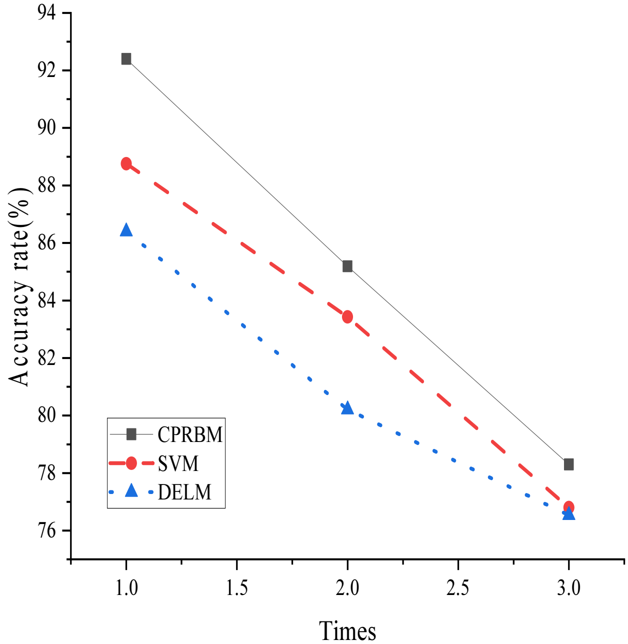

Figure 9. Accuracy comparison of different models

5. Conclusion

The export credit risk assessment system based on the deep belief network is studied to reduce the export credit risk of enterprises under the Belt and Road Initiative and improve the sustainable development of the economy. First, the current status of the research on the export credit risk and the deep belief network based on deep learning are introduced. Second, the supervised learning method of the restricted Boltzmann machine is studied. On this basis, the comparative divergence algorithm is improved, and the classification partition RBM algorithm is constructed. Finally, the empirical study of the algorithm is carried out. The results show that the algorithm constructed has a good application effect. However, there are still some shortcomings that need to be improved. That is, the running speed of the constructed algorithm is not considered. The running speed of the constructed algorithm will be the focus of the follow-up research.

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